

# Developing Cognitive Advisor Agents for Operators in Industry 4.0

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## Abstract

Human cyber-physical systems (CPS) are an important component in the development of Industry 4.0. The paradigm shift of doing to thinking has allowed the emergence of cognition as a new perspective for intelligent systems. Currently, different platforms offer several cognitive solutions. Within this space, user assistance systems become increasingly necessary not as a tool but as a function that amplifies the capabilities of the operator in the work environment. There exist different perspectives of cognition. In this study cognition is introduced from the point of view of joint cognitive systems (JCSs); the synergistic combination of different technologies such as artificial intelligence (AI), the Internet of Things (IoT) and multi-agent systems (MAS) allows the operator and the process to provide the necessary conditions to do their work effectively and efficiently.

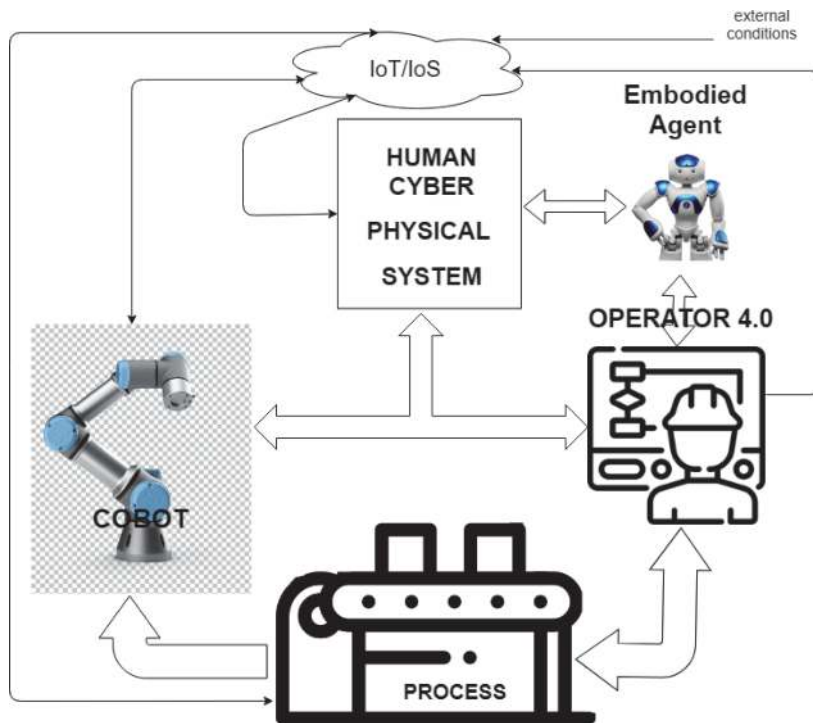
**Keywords:** cognition, multi-agent system, advisor, operator

## 1. Introduction

The continuous introduction of technology in the industrial environment is a main generator of changes in architectures, models and work styles in the industry. Currently, Industry 4.0 signifies a great opportunity for operators to become a part of the new manufacturing systems [1]. On the one hand, operators generate information and data to programme machines and robots and optimise process flows; on the other hand, they receive useful support for their work as well as effective cooperation with intelligent systems [2]. This bidirectional dialogue allows new types of powerful interactions between operators and machines. Hence, a new kind of workforce should be trained in order to obtain a significant impact on the development of the industry [3].

The use of artificial intelligence (AI) techniques to enhance the lifelong learning experience of humans has evolved in literature from the early works on *intelligent tutor systems*, where AI is used as a tool to monitor and facilitate the user learning process, to the creation of *human-computer collaborative learning* systems (HCCL) [4], where AI entities become members of a group of mixed human and artificial learners. Through HCCL systems, humans acquire problem-solving or decision-making capabilities in a particular domain in simulated or real situations.

In the Industry 4.0 scenario, AI entities can be endowed as cognitive advisor agents implemented in the form of either voice assistants or embodied agents, in



**Figure 1.** Proof of concept. The operator 4.0 is assisted by the embodied agent to collaborate with the cobot in the process.

order to propose collaborative working behaviours between machines and humans. The implementation of these systems in manufacturing pushes towards factories characterised by the symbiosis of human automation [5], where machines cooperate with humans, both parts having the opportunity to lead the cooperative task at hands.

The challenge motivating this research is to define a human-centred architecture to design, implement and evaluate cognitive advisor agents in the framework of a human cyber-physical production system (H-CPPS) [2, 6] which supports the operator in Industry 4.0 to accomplish their job into an automation system [7] in a more efficient and effective form. The proposed overall H-CPPS architecture will be evaluated through a proof of concept based on a multi-agent system (MAS) implementing a cognitive robot (embodied agent) to assist the operator (operator 4.0) in a collaborative work with a cobot. A scheme of the operator—cobot—assistant robot symbiotic system is shown in **Figure 1**.

This chapter is structured as follows. Firstly, the current Industry 4.0 paradigm is introduced, and the role of human operator in this domain is shown. Next, the proposed human cyber-physical production system architecture is introduced. Moreover, the approach of this architecture to cognitive tasks is presented. The cognitive advisor vision to be endowed into the previous architecture is finally introduced. Conclusions and future research lines are closing the chapter.

## 2. The operator’s workspace in Industry 4.0

The *operator 4.0* concept is defined in [2, 8] in a general form as an operator in an industrial setting assisted by technological tools. Although the increase in the degree of automation in factories reduces costs and improves productivity, in the Industry 4.0 vision, differently of computer-integrated manufacturing (CIM),

human operators are yet key elements in the manufacturing systems. In fact, the increasing degree of automation ‘per se’ does not necessarily lead to enhanced operator performance.

The continuous innovations in the technological areas of cyber-physical systems (CPS), the Internet of Things (IoT), the Internet of Services (IoS), robotics, big data, cloud and cognitive computing and augmented reality (AR) result in a significant change in production systems [9, 10]. Empowered with these new skills, cyber-physical systems can take part, for instance, in tasks of planning and disposition, eventually to manage them. Machines take care of the adequate supply of material, change the production method to the optimal one for the real product or devise a new plan themselves [11]. This technological evolution generates, among others, the following impacts on the operator:

- The qualification of manual tasks decreases.
- The operator can access all the necessary information in real-time to take decisions.
- Intelligent assistance systems allow decisions to be taken more quickly and in a short space of time.
- Co-working in the workspace between machines and people requires less effort and attention.
- Human implementation and monitoring are more relevant than ever.

The emerging technologies in Industry 4.0 [12] as well as current development of AI technologies are allowing that cyber-physical systems oriented to human-machine interaction be moving from only a physical interaction vision paradigm to also a cognitive one (see **Table 1**). The operator should be able to take the control and supervise the automated production system. However, the increasing information and communication power of these systems leads to a complexity that is not understandable by the current standard user interfaces employed in the industry. Consequently, the operator would need support to keep the system under stable requirements. Moreover, the operator could get the system work plan (factory, not shift supervisor), and therefore the operator would need additional information during field operation, which requires access to location-independent information as well as a situation-oriented and task-oriented information offer [13].

As a result of this paradigm shift, new forms of interaction appear in the field of human-machine interface (HMI), in the form of intelligent user interfaces, such as operator support systems (OSS), assistance systems, decision support systems and intelligent personal assistants (IPAs) [7]. In the context of smart, people-centred service systems, cognitive systems can potentially progress from tools to assistants to collaborators to coaches and be perceived differently depending on the role they play in a service system.

	Physical	Cognitive
Routine	Traditional automation	Automated learning techniques
Nonroutine	Collaborative robots	Intelligent assistants (IA)

**Table 1.**  
*Vision of physical and cognitive automation.*

Assistance systems support the operator as follows [14]:

- From a human-centred design approach, it expressly considers the identification of user context, the specification of user requirements, the creation of design solutions, and the evaluation of design solutions. Moreover, it provides an appropriate amount of information in a clear way.
- As a decision-maker in production control, with information acquisition, data aggregation/analysis of information and operation choice.

However, it should be clarified that the final decision always remains in the human operator side, thus maintaining the principle of human centrality.

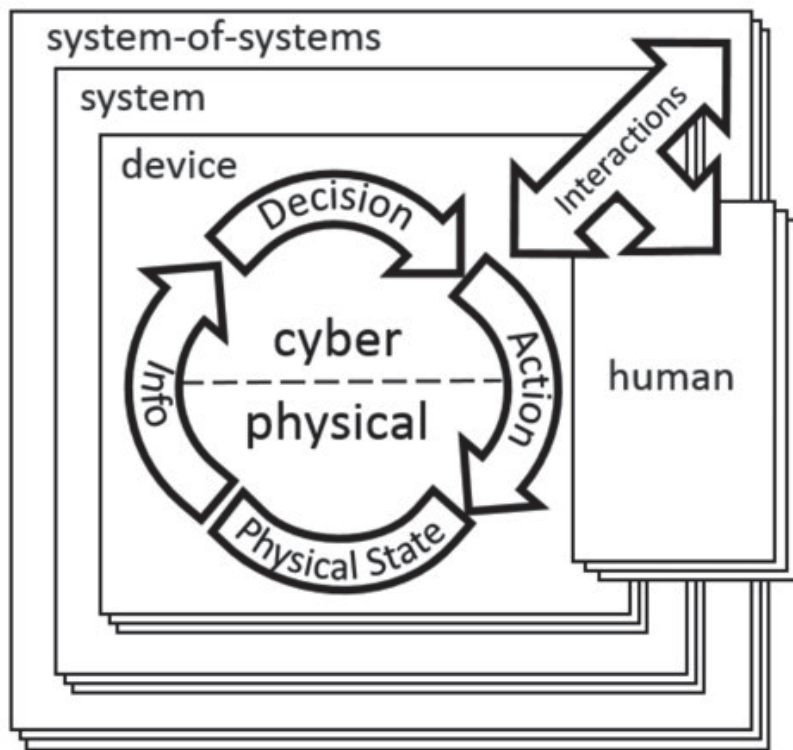
Regarding the tasks and the role of the operator, an increase in the proportion of *complex cognitive tasks* is expected, hence increasing the needs for coordination or organisation of production resources, as well as the control and monitoring of complex production systems.

The literature shows that a significant change in this relationship from purely physical to cognitive refers to the human-machine interface, which encompasses the interaction between operators and a set of new forms of collaborative work. The interaction between humans and CPS is produced by either direct manipulation or with the help of a mediating user interface. Such a close interaction between humans and CPS also raises socio-technological issues regarding autonomy and decision-making power. Cybernetics provides an answer on how a system that controls another system can compensate for more errors in the control process by having more operational variety. As the most flexible entity in the cyber-physical structure, the human will assume the role of a higher-level control instance [10]. Through technological support, it is guaranteed that operators can develop their full potential and adopt the role of strategic decision-makers and flexible problem solvers, thus managing the increasing technical complexity.

### **3. Human cyber-physical production systems**

Cyber-physical systems are one of the fundamental pillars of Industry 4.0 [10, 15, 16]. According to the National Institute of Standards and Technology (NIST), cyber-physical systems are intelligent systems, including interactive networks, designed of physical and computational components. These systems integrate computing, communication, detection and performance with physical systems to fulfil time-sensitive functions with varying degrees of interaction with the environment, including human interaction (see **Figure 2**). These systems are conceived as components in the production system able of executing physical processes in cooperation with other entities. Systems can adapt independently to changing circumstances, by learning from the additional information coming from the sensors [6].

Usually, each component of the CPS takes the necessary control decisions related to the physical aspects of the underlying production system and communicates control decisions, system states and behaviour patterns. Currently, the possibility to combine existing technologies such as multi-agent systems, service-oriented architectures (SOA), the Internet of things, cloud communication, augmented reality, big data or machine-to-machine communication (M2M) [9] has empowered the features and functions of these systems so that levels of cognition in the cooperation, beyond physical interaction, can be also considered.

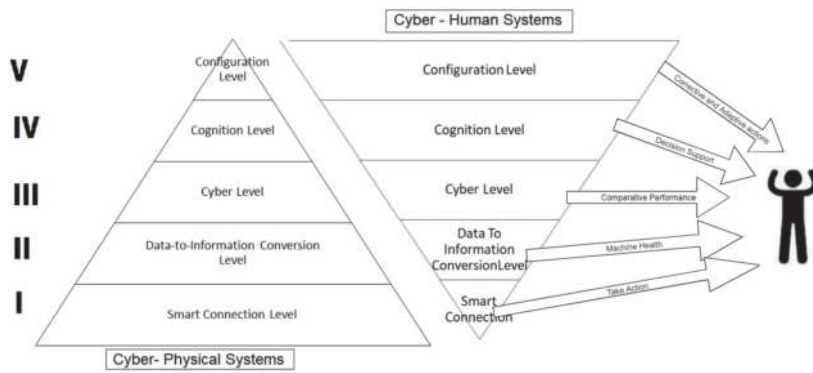


**Figure 2.**  
CPS conceptual model [17].

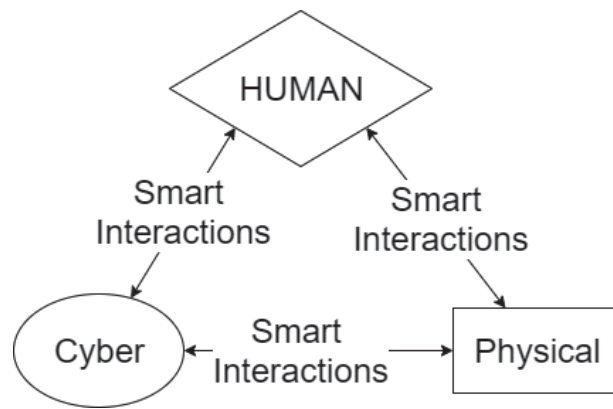
In the approach with humans in the interaction, new models of CPS have emerged which focused on improving the capabilities of operators, such as cyber-physical human system (CPHS) [17] and human cyber-physical production system [2]. CPHS is defined as “a class of sociotechnical systems critical for security in which the interactions between the physical system and the cybernetic elements that control its operation are influenced by human agents.” Our research, however, focuses on H-CPPS, defined as “a work system that improves the capabilities of operators thanks to a dynamic interaction between humans and machines in the cyber and physical worlds through intelligent human-machine interfaces.” The objectives for H-CPPS are achieved through the interactions between the physical system (or process) to be controlled, cybernetic elements (i.e. communication links and software modules) and human agents that monitor and influence the functioning of the cyber-physical elements.

In both definitions we can highlight the role of the operator within the control loop. In human-oriented architectures, there is the ability to feedback the information (see **Figure 3**) at each level, because inherent intelligence of human operators can be used naturally for self-adaptation, corrective and preventive actions. For the H-CPPS approach, its levels’ configuration acts as a supervisory control to ensure that decisions made at the cognitive level are implemented and that corrective or adaptive actions are carried out by the human worker [18].

H-CPPS are very dynamic and complex systems being subject to a certain degree of unpredictable behaviour of both the environment and the user. These conditions generate several challenges related to the administration of H-CPPS that require run-time capabilities allowing the system to detect, monitor, understand, plan and act on those not predicted changes while minimising (and potentially eliminating) system downtime. In order to develop our cognitive advisor agent for operators, we start by defining three dimensions of H-CPPS: *cybernetic*, *physical* and *human*. Each



**Figure 3.**  
CPS vs. H-CPPS model.



**Figure 4.**  
Three dimensions of H-CPPS.

dimension is connected to the other ones through intelligent interactions (see **Figure 4**).

The physical dimension includes all the resources connected to the production system through sensors and actuators. The cybernetic dimension describes all computing, network and cloud infrastructures that communicate data, processes and software resources. Finally, the human dimension describes human elements, as well as their situations based on their objectives and context. The human dimension is especially relevant for this research, focused in aligning the objectives of H-CPPS with the achievement of the personal goals of the users.

### 3.1 Agent-based approach to H-CPPS

The applications of artificial intelligence techniques related to humans in the work environment are guided by four possible paths in human cyber-physical systems (see **Table 2**). As the ‘human in the loop’ is considered in H-CPPS, intelligent assistance systems are the approach to be developed in our research.

Nowadays, different architecture patterns and implementation technologies have been developed and applied to process and exchange information allowing H-CPPS components to make their decisions. They range from service-oriented architectures that exploit technologies such as web services to agent-based architectures that exploit solutions compatible with Foundation for Intelligent Physical Agents (FIPA) [19]. However, they also come with their own set of challenges.

	Human in the loop	No human in the loop
Hardwired specific systems	<i>Assisted intelligence:</i> AI system that assist human in making decisions or taking actions, hardwired systems that do not learn from their interactions	<i>Automation:</i> Automation of manual and cognitive tasks that are either routine or nonroutine. This does not involve new ways of doing things—automates existing task
Adaptative systems	<i>Assisted intelligence:</i> AI systems that augment human decision-making and continuously learn from their interactions with humans and the environment	<i>Autonomous intelligence:</i> AI systems that can adapt to different situations and can act autonomously without assistance

**Table 2.**  
 Path AI in human cyber-physical systems.

Multi-agent systems [20] are an example of architecture applicable to the implementation of H-CPPS. More specifically, industrial agents [21, 22] address industry requirements in productive systems. MAS expose system characteristics such as autonomy, cooperation, intelligence, reactivity and proactivity, which allows intelligence to be distributed among a network of control nodes and, consequently, adapts effectively to distributed control systems, that is, by implementing H-CPPS solutions [21]. While the use of MAS for control process can be considered as a mature architecture pattern, its application in the industry is still limited [23].

In order to define our agent-based approach to H-CPPS systems, two types of interactions should be identified (see **Figure 4**):

- Interaction between agents (only considering the cyber dimension)
- Interaction between agents (cyber dimension) and hardware automation control devices (physical dimension)

For the first type of interaction, FIPA has established guidelines to regulate the development of agent-based systems. It is a collection of standards that are grouped into different categories, that is, applications, summary architecture, agent communication, agent management and message transport agent. For the second type of interaction, related to the interconnection of the agent and the physical automation control device [24], standardised practices are not yet defined, allowing to simplify and make transparent the process of integration of physical and cybernetic counterparts.

Finally, it should be noticed that agents, as an enabling technology to manage smart approaches, endow inherent characteristics (including autonomy, negotiation, mobility) which could be more beneficial when combined with *distributed intelligence* approaches and lead to better services and applications at the edge [16].

### 3.2 Human roles in H-CPPS

For the moment, the cyber and the physical dimension have been considered in our agent-based approach. However, while in a human-centred architecture, the roles of humans in cyber-physical human systems (H-CPPS) must be also defined.

In the models of human-automation interaction, attention is paid to whether human assumes control of the system [25]. In H-CPPS systems, however, human intervention is focused in more aspects: the dialogue with other agents, decision-making and information supply. In this sense, one research line is about the definition of a human model as a part of the full H-CPPS model. However, human models defined as a transfer function leads to a poor approach. Some researchers expand

this approach by developing analytic human models that reflect *cognitive abilities* in the interaction with cyber-physical systems [17]. On the other hand, a H-CPPS requires flexibility. An adaptive H-CPPS responds to unexpected or novel situations (replanning, setting new goals, learn from experience), and the definition of the role of human (passive or active performer) is required [17]. Human roles examples in H-CPPS are, for instance:

- Supervisor (human on the loop): Approve CPS decisions; reallocate tasks between human and CPS.
- Controller (human in the loop, operator 4.0): Interact with sensors and actuators; use of augmented reality technology; collaborative task with a cobot.

Merging human roles with CPS roles in order to define the functional architecture of a H-CPPS leads our research to the definition of a *joint cognitive system* (JCS), its basic aim being to achieve a high level of successful performance managing the human cognitive load in the process.

#### **4. Joint cognitive system**

The current development of technology allows us to reach the level of cognition in H-CPPS (see **Figure 3**) [18]. However, the understanding of cognition generates debates because it can be approached from several domains, mainly from psychology through mental models, and from cognitive systems engineering (CSE) to applications in practice.

A joint cognitive system acknowledges that cognition emerges as goal-oriented interactions of people and artefacts in order to produce work in a specific context and at the level of the work being conducted. It does not produce models of cognition but models of **coagency** that corresponds to the required variety of performance and thereby emphasises the functional aspects [26].

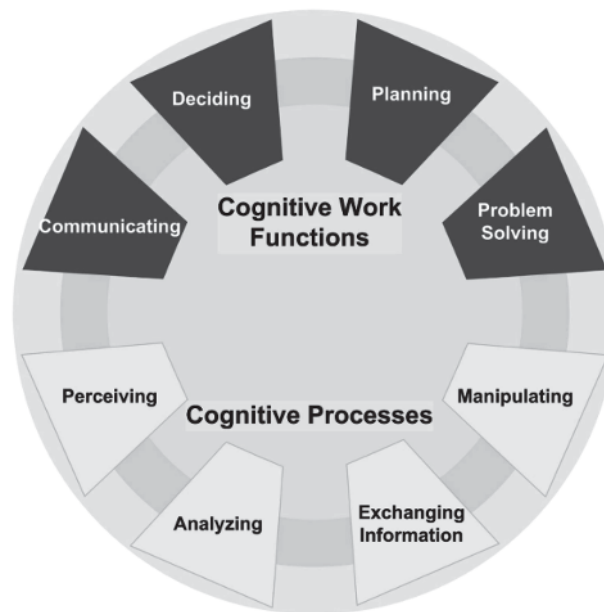
In this situation, complexity emerges because neither goals nor resources nor constraints remain constant, creating dynamic couplings between artefacts, operators and organisations. The CSE approach focuses on analysing how people manage complexity, understanding how artefacts are used and understanding how people and artefacts work together to create and organise joint cognitive systems which constitutes a basic unit of analysis in CSE. Human and machine need to be considered together, rather than separate entities linked by human-machine interactions [27].

In the domain of CSE, focus is on the mission that the joint cognitive system shall perform, avoiding vagaries into its human resemblances. It performs cognitive work via cognitive functions such as communicating, deciding, planning, and problem-solving (**Figure 5**). These sorts of cognitive functions are supported by cognitive processes such as perceiving, analysing, exchanging information and manipulating.

The importance of cognition, regardless of how it is defined, as a necessary part of the work has grown after the industrial revolution:

- Cognition is distributed rather than isolated in the human operator's mind.
- Operator does not passively accept technological artefacts or the original conditions of their work.





**Figure 5.**  
*Cognitive work functions and cognitive processes.*

- Technological development is rampant; this entails the development of work with inevitably greater *operational complexity*.
- Technology is often used in ways that are not well adapted to the needs of the operator.

There is no turning back, the evolution of information technology, digital transformation and the Fourth Industrial Revolution requires that processes be more cognitive, automatic and efficient.

#### 4.1 The cognitive design problem: the FRAM tool

As the automation of complex processes becomes more achievable, the need for engineering procedures that help decide what and how to automate becomes more important to the safety, flexibility and performance of automation use. The implementation must satisfy general criteria such as *minimising workload*, *maximising awareness of what is going on* and *reducing the number of errors*. The basic problem therefore is to reduce the cognitive demands of the tasks being performed by the operators involved in the system while maintaining fully their ability to function within their given roles [28].

JCSs are characterised by three principles [27]: (a) goal orientation, (b) control to minimise entropy (i.e. disorder in the system) and (c) coagency at the service of objectives.

In order to understand the sociotechnical system, the functional resonance analysis method (FRAM) [29] can be used, which allows to have a model generated by the application itself. The FRAM can be described as a method that is used to produce a model, instead of a method that is derived from a model. It proposes that everyday events and activities can be described in terms of *functions* involved without predefined specific relations, levels or structures. Instead, the FRAM assumes that the behaviour of functions, hence the outcomes of an activity or

process, can be understood in terms of *four basic principles* described in the following statements. Moreover, the not predefined functions are described using *six aspects*.

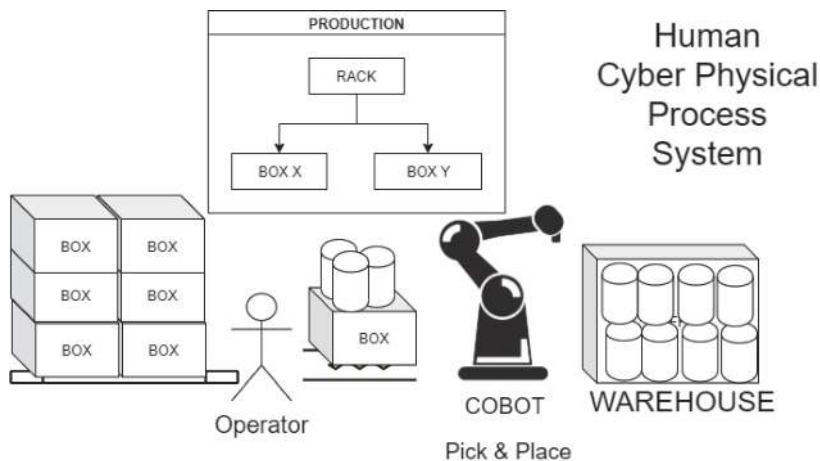
The principles of FRAM are:

1. The equivalence of successes and failures: acceptable outcomes as well as unacceptable outcomes are due to the ability of organisations, groups and individuals successfully to adjust to expected and unexpected situations.
2. Approximate adjustments: things predominantly go well, but also they occasionally go wrong.
3. Emergent outcomes: the variability of two or more functions can be combined in unexpected ways that can lead to results that are unpredictable and disproportionate in magnitude, both negative and positive.
4. Functional resonance: the variability of one function may in this way come to affect the variability of other functions in analogy with the phenomenon of resonance.

In FRAM a function represents acts or activities—simple or composite—needed to produce a certain result. Examples of simple human functions are to triage a patient or to fill a glass with water. The organisational function of the emergency room in a hospital, for example, is to treat incoming patients, while the function of a restaurant is to serve food. Finally, composite functions include, for instance, a flight management system.

In the description of functions, an important distinction can be made between tasks and activities, corresponding to the distinction between work-as-imagined (WAI) and work-as-done (WAD). A task describes work as designed or as imagined by managers. An activity describes work as it is actually performed or done. FRAM primarily focuses on activities as they are done or WAD but can of course also be used to model WAI.

To basically illustrate the use of FRAM, a pick and place system with a robot is shown in **Figure 6**. The system is based on filling boxes with cylinders. The cylinder supplier is in position *Warehouse* and the destination box in position *Box*. The FRAM model should describe functions and their potential couplings for a typical

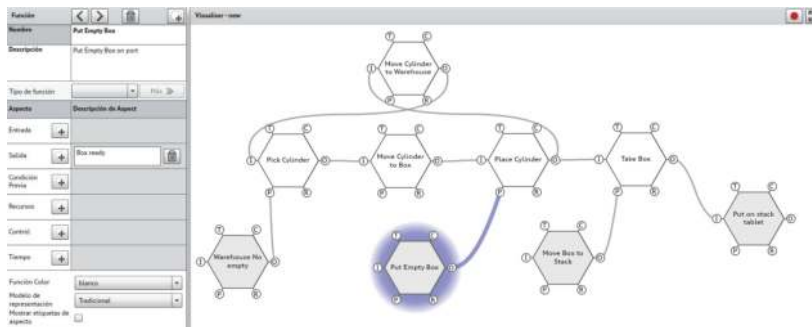


**Figure 6.**  
Example of a H-CPPS.

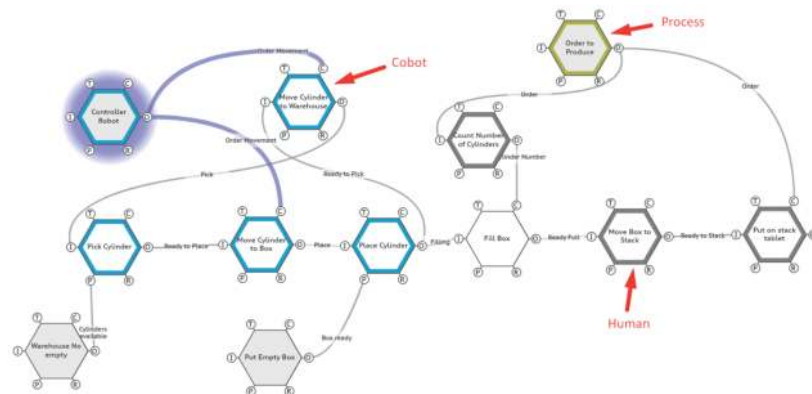
situation but not for a specific one. Hence, it is not possible to certainly determine whether a function always will be performed before or after another function. It can only be determined when the model is instantiated. At the start, functions are identified in a first-independent version about execution (see **Figure 7**).

The development of the model can continue in several ways—none of them being preferable over the others. One way is to look at the other functions in the same way and try to define as many of their aspects as seems reasonable and possible. Another way is try to define aspects that are incompletely described in the current version of the model. The basis of the FRAM is the description of the functions that make up an activity or a process. The functions of different tasks have been assigned depending on who does it, (human, cobot, process) in the H-CPPS (see **Figure 8**). The relationships are not specified nor described directly, and the FRAM Model Visualiser (FMV) in fact does not allow lines or connectors to be drawn between functions. The relationships are instead specified indirectly via the descriptions of the aspects of functions. The common technical term for such relations is *couplings*.

Couplings described in a FRAM model through dependencies are called *potential couplings*. This is because a FRAM model describes the potential or possible relationships or dependencies between functions without referring to any particular situation. In an instantiating of a FRAM model, only a subset of the potential couplings can be realised; these represent the *actual couplings* or dependencies that have occurred or are expected to occur in a particular situation or a particular scenario [29].



**Figure 7.**  
 The FRAM model for a pick and place function ver1.0.



**Figure 8.**  
 The FRAM model for a pick and place function/assignment functions.

Hence, basically we can highlight the following useful features for our study:

- **Purpose:** A FRAM analysis aims to identify how the system works (or should work) for everything to succeed (i.e. everyday performance) and to understand how the variability of functions alone or in combination may affect overall performance.
- **Model:** A FRAM model describes a system's functions and the potential couplings among them. The model does not describe or depict an actual sequence of events, such as an accident or a future scenario.
- **Instantiation:** A concrete scenario is the result of an instantiation of the model. The instantiation is a 'map' about functions coupling or how they may become coupled, under given—favourable or unfavourable—conditions.

The use of FRAM as a tool for the analysis of cognitive tasks would allow us to understand about JCS works, identify its critical points and the propagation of the relationships between functions and understand the distributed cognition and coagency between the human and the machine.

## **5. Cognitive advisor agents**

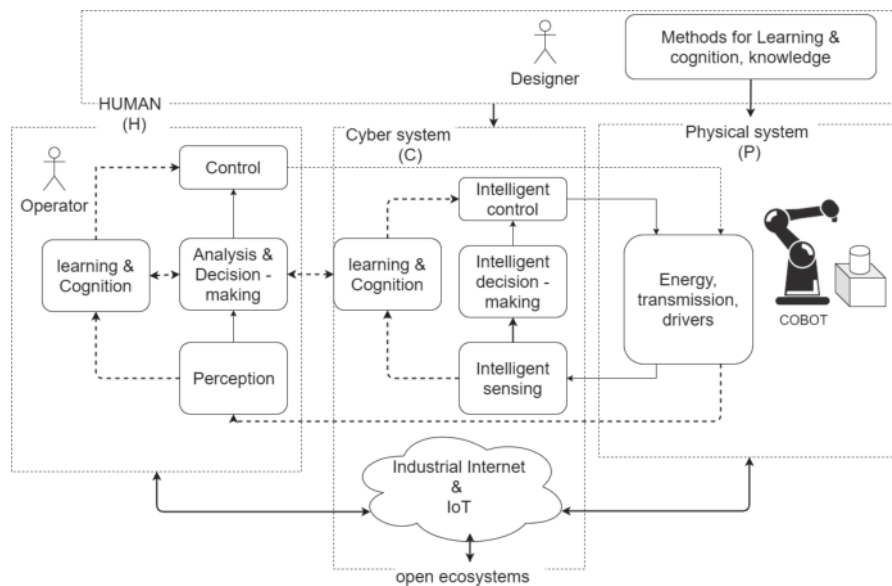
Cognitive systems are capable of humanlike actions such as perception, learning, planning, reasoning, self- and context-awareness, interaction and performing actions in unstructured environments. The functionality of the cognitive system includes enabling perception and awareness, understanding and interpreting situations, reasoning, decision-making and autonomous acting.

Due to their cognitive capabilities, humans are superior to fully automated mass production systems in adapting to flexible, customised manufacturing processes. Yet, the increasing specialisation is creating more and more complex production processes that require elaborate assistance in task execution. Furthermore, machines are much better at performing repetitive, heavy-load tasks with high precision and reliability.

The cognitive system provides the best possible assistance with the least necessary disruption. In this context, a cognitive system enables the realisation of an adaptive, sensitive assistance system that provides guidance only if needed and based on operator skill (e.g. a 1-day 1 trainee versus a worker who has been with the company for 30 years), cognitive load and perception capability—in other words, it provides the best possible assistance with the least necessary disruption. The adaptivity of the feedback design enables the education of novices in on-the-job training scenarios, integrating novices directly into the production process during their 1-month training period without the need for specialists [30].

At present, H-CPPS can be endowed with powerful intelligence by leveraging next-generation AI, which allows three main technological features: the first, most critical, characteristic is that the cyber systems have the ability to solve uncertain and complex problems; furthermore, problem-solving methods shift from the traditional model of emphasising causality to an innovative model of emphasising correlation and further towards an advanced model of deeply integrating correlation with causality. This shift will lead to fundamental improvements in the modeling and optimization of manufacturing systems.

The second most important feature is that cyber systems have capabilities such as learning, cognitive skills and the generation and better use of knowledge; this will



**Figure 9.**  
*H-CPPS for Industry 4.0.*

lead to revolutionary changes in the efficiency of the generation, use, importation and accumulation of knowledge and to the significant promotion of the marginal productivity of knowledge as a central productive element.

The third feature is the formation of augmented human-machine hybrid intelligence, which provides full scope and synergistically integrates the advantages of human intelligence and artificial intelligence. This will result in the innovation potential of humans being completely released, and the innovation capabilities of the manufacturing industry greatly increase. With these technological advances and the advances in the Internet of Things and cloud computing, cognitive solutions are available that will allow the operator to develop their work in an efficient, effective and, above all, empowered position. **Figure 9** introduces an architecture with cognition for the Industry 4.0. Two characteristics are important to highlight, the first the Internet of Things and its solutions in the cloud which allow to reach levels of cognition for all operator functions and the second the cognitive capacity of H-CPPS systems.

## 6. Conclusions

The development of emerging technologies around Industry 4.0 is changing the paradigm of the intelligent industry to the cognitive industry, where it seeks to harness the cognitive capabilities of the systems to meet the new demands of the industry. Challenges presented by technological development that focused on industry require the integration of different areas of science, engineering and technology. Today, synergy combinations are required to support the development of intelligent and cognitive solutions. Understanding of sociotechnical systems from the perspective of joint cognitive systems shows in the first place the current ability to provide the operator with functions and tools that allow him to amplify his abilities, in particular the cognitive ones for which it can be seen that there are different cognitive tools, thanks to which cognitive solutions are capable of being applied.

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